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Arbitrage constraints and behaviour of volatility components: Evidence from a natural experiment*

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Preliminary and evolving version

Abstract

Short-selling constraints are known to impede information flow into the financial markets, particularly that of negative information. We employ "Regulation SHO" as a natural experiment to examine how the lowering of short sale constraints impacts the information flow. Specifically, we investigate whether large and small volatility jumps significantly change around the regulatory change, for the treated (Pilot) and control-group (non-Pilot) stocks. We find that large (small) jumps significantly decline (rise) as an outcome of the relaxation of short sale constraints, despite an increase in the variance of the Pilot stocks. The decline in the intensity of large jumps and the simultaneous increase in the intensity of small jumps suggest more efficient information flow into the market. Furthermore, the decline is larger for firms facing greater short-sale constraints, indicating that the impact of short-sale constraints are more pronounced for them. Implying that the change in the jump components is brought about by the easing of the short sale constraints, we also find that the decline in the large jump intensity is higher for firms with lower conservatism in information disclosure.

Key words: Regulation SHO, Short-sale constraints, Arbitrage, Volatility jumps

JEL Codes: G11, G12, G14

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1. Introduction and Motivation

The jump component of integrated volatility is known to be linked to frictions in the information flow of financial assets. For instance, Miao, Ramchander, and Zumwalt (2014) find that S&P 500 index futures jump in response to macroeconomic news. Boudt and Petitjean (2014) find that stock price jumps in the Dow Jones Industrial Average constituents are accompanied by an increase in trading costs and amplified by the release of the news. Aman (2013) finds that in the Japanese equity market, firm-specific news leads to increased crash risk. Rangel (2011) finds that macroeconomic shocks cause jumps in the stock market.[1] Given the above evidence, it is likely that an intervention that changes the flow of stock-specific information, such as relaxation of short-selling constraints, would impact jumps in stock returns. As market frictions cause changes in the jump components of observed volatility, it is also likely to be significantly impacted by the events that increase short-selling in stocks.

In this paper, we examine the causal influence of short-sale constraints on the jump intensity of stock returns by investigating the changes in jump intensity associated with Regulation SHO in the US market. Regulation SHO eased short-selling constraints for a randomly selected set of stocks by removing the 'uptick rule'[2]. As Regulation SHO eased short-selling constraints on a select group of stocks (called Pilot stocks) for a certain period of time (called Pilot period), examining its impact on jumps would allow a causal interpretation. We utilise the Regulation SHO program as a natural experiment to examine if the intensity of large jumps, both positive and negative, decreases for the Pilot stocks. We also examine the extent to which any decline in large jumps is associated with short-selling constraints.

As short selling allows negative information to be incorporated into the asset prices, asset prices are expected to be impacted by the relaxing of short selling constraints. For instance, Boehmer and Wu (2013) show that stock prices have greater accuracy when

[1] Closely related research has documented that the jump component of volatility also has origins in the macroeconomic news. Bomfim (2003); Das (2002) find that Fed interventions are a source of surprise jumps in interest rates

[2] A rule that restricts short-selling only to instances where the price is on an uptick.

short sellers are more active. Boehmer, Jones, Wu, and Zhang (2019) find that it is the analyst and earnings-related news that lead to the under-performance of heavily shorted stocks. Massa, Qian, Xu, and Zhang (2015) show that in the presence of short sellers, insiders trade faster. Short selling is known to be constrained across financial markets for a variety of reasons including borrowing constraints (see Gromb & Vayanos, 2010; Porras Prado, Saffi, & Sturgess, 2016). Saffi and Sigurdsson (2011) find that an increase (decrease) in lending supply (lending fee), which indicates a lowering of short sale constraints, leads to increased market efficiency. Using an event where short-sale constraints are eased in China, Chang, Luo, and Ren (2014) show that price efficiency increases and the frequency of extreme stock return reduces. In a cross-country study, Bris, Goetzmann, and Zhu (2007) find that the price efficiency of stocks is lower in markets where short sales are either not allowed or are not practised. Alexander and Peterson (2008) find that removal of the uptick rule for the Pilot stocks led to a quicker execution of trades and more aggressive trading, leading to better price efficiency. Overall, the literature documents a more efficient price discovery when short-sale constraints are relaxed.

Several studies use Regulation SHO to study asset prices. In particular, these studies use the fact that a randomly selected group of stocks had short selling constraints relaxed for three years, which could be used to examine the impact on asset pricing and managerial behaviour. For instance, Chu, Hirshleifer, and Ma (2017) employ the pilot program to show that certain asset pricing anomalies were reduced during the pilot period for the pilot stocks, due to the easing of short selling constraints. Li and Zhang (2015) show that managers of the pilot firms lowered the precision of bad news, as price sensitivity to bad news increased due to the easing of short selling constraints. Deng, Gao, and Kim (2020) find that the stock price crash risk declined for the Pilot firms and more so for firms with poor bad news reporting. Gong (2020) finds that the Pilot firms follow a more conservative financing policy in response to the increased threat of shorting of the stock.

Several papers examine the impact of Regulation SHO and other instances involving the relaxation of short sale constraints on volatility. For instance, Diether, Lee, and

Werner (2009) found that volatility increased for NYSE stocks in response to the Regulation SHO. Crane, Crotty, Michenaud, and Naranjo (2019) find that a selective ban on the short sale of stocks in the Hong Kong market does not lead to a change in crash risk or volatility between the two sets of stocks. Given that volatility could be bifurcated to jump and diffusion components, it is possible to gain useful insights into how the relaxation of short-selling impacts market efficiency, in terms of the components of volatility. Yeh and Chen (2014) find that short selling constraints lead to a larger downward jump size, while the upward jump size does not change in the Taiwanese market. Our study utilizes a similar setup in the US to examine the impact of a regulatory change on the jump components of the volatility of stock returns. We also examine whether relaxing the short sale constraints leads to a greater decline of large jumps in stocks that are likely to be more short-sale constrained. This would indicate an incremental improvement in the market quality of such stocks. Furthermore, we also investigate the link between managerial action and the behavior of jump components as a response to the change in short-sale constraints. Specifically, we follow Deng et al. (2020) and examine if stock of firms that followed less conservative accounting policies, had a greater reduction in their large jump volatility. The examination would indicate that the threat of short sellers leads to an improvement in the information environment of a firm.

To examine the behaviour of the jump components, we decompose the total volatility of each stock into its components, large and small positive and negative jumps, and a continuous component, similar to Barndorff-Nielsen, Kinnebrock, and Shephard (2008) and Patton and Sheppard (2015). We use the daily returns of all the stocks listed on NYSE and NASDAQ from 1998 to 2018 to compute monthly return volatility and its components. We then examine whether large jumps decline for Pilot stocks during the Pilot period and all stocks in the post-Pilot when short selling constraints were relaxed for all stocks. We employ a difference-in-differences (DiD) analysis, where the Pilot (non-Pilot) stocks are the treatment (control) group. We also examine the heterogeneous impact of Regulation SHO on the components of volatility, where we employ a difference-in-differences-in-differences (DiDiD) analysis. Particularly, we investigate whether stocks that are more likely to face short-sale constraints have a greater decline in large jumps and an increase in small jumps.

Our key findings and their implications are as follows. First, we find that in response to the relaxed short sale constraints for Pilot stocks, both the positive and negative large jump intensities (PLJ and NLJ respectively) significantly decline and the positive and negative small jump intensities (PSJ and NSJ respectively) significantly increase in the Pilot period. For instance, NLJ (NSJ) for the Pilot stocks in the Pilot period was 1.7% lower (2.1 % higher) compared to the non-Pilot stocks. The decline of the large jumps indicates a more efficient flow of price-sensitive information into the prices in the treatment period. In addition, we also find that when the short sale constraints are relaxed for all stocks, large (small) jumps decrease (increase) for all the stocks. The finding is in line with that of Yeh and Chen (2014) in the Taiwanese market. Furthermore, we also find that the decrease in NLJ is almost twice in magnitude (1.4%) compared to the decrease in the PLJ (0.7%), indicating that the decrease in the jump component is more pronounced on the negative side. The finding can be reasoned within the short-sale constraints framework, as the easing of short-selling constraints incorporates negative news more swiftly into the prices. Our main results are robust to both firm and time-fixed effects and also to various alternative definitions for identifying large jumps. We also show that the significant decline in large jumps is an outcome of the relaxation of the uptick rule, as such an effect is absent during several placebo test periods.

Second, we show that the observed decline in the jump intensities in response to the Regulation SHO program is greater for stocks that are likely to face higher short-sale constraints. In particular, we employ three firm-specific proxies for arbitrage constraints, firm size, the proportion of shares held by institutional investors, and Amihud's illiquidity (see Amihud, 2002) in the year before the treatment period. We find that firms that are likely to face higher short-selling constraints had a greater decrease in the large jumps (both NLJ and PLJ) and a simultaneous greater increase in their small jump intensities. For instance, Pilot firms with below median institutional ownership realised a higher drop in their NLJ to the extent of 2.4 %, relative to the firms with higher institutional ownership. For comparison, the average drop in the NLJ of Pilot stocks was 1.4 %. The finding suggests relaxing the short sale constraint made the flow of information more efficient for firms with greater short-sale constraints. The relative decline in the large jump intensities for firms that are more likely to be short-sale constrained is in line with studies on short-selling constraints and firm characteristics. For instance, D'avolio (2002) finds that the "specialness" of a stock, its ability to sustain high loan fees and therefore have high arbitrage constraints, is lower for stocks with larger institutional holdings and the stocks of bigger firms.

Finally, we find evidence that managerial action in the face of increased threat of short sellers leads to the observed decrease in the large jumps. It is likely that as the threat of short selling increases in the market firms that were less conservative in the pre-event period would become more conservative in their disclosures in the Regulation SHO period, by improving the quality of disclosures. We find evidence in support of this hypothesis. For instance, firms with an below-median score of accounting conservatism, measured by CScore (see Khan & Watts, 2009) experienced a decline in NLJ that was 1.38% higher relative to a firm with above median CScore. The difference in the magnitude of the decline of large jumps, between the two sub-samples is significant given that the average decrease for a Pilot firm was only 1.4%. The evidence is also in line with Deng et al. (2020) who find that firms with lower accounting conservatism experienced a larger decline in the crash risk of stocks.

Our finding of the change in behaviour of the jump components during the Regulation SHO and its variation across stocks significantly contributes to the related findings in several other papers. Firstly, the paper establishes that Regulation SHO, which eases the arbitrage constraints has strongly impacted the behaviour of the jump components of volatility. The earlier papers on the issue (eg. Yeh & Chen, 2014) have not examined how the large and small jump components of volatility change on relaxing the short-sale constraints. Particularly, we demonstrate that the relative decline in the negative large jumps is of a greater magnitude compared to that of the positive large jumps, reflective of the direct impact of the regulation on the flow of negative information. Furthermore, the paper also brings out that the changes in the large and small jumps are more pronounced for firms that are more likely to face greater arbitrage constraints, such as small firms and firms with lower institutional ownership. The paper thus significantly deepens the insights on the impact of the regulation on asset returns brought about by earlier papers. For instance, Chu et al. (2017) find that the asset pricing anomalies weaken in Pilot stocks compared to the non-Pilot stocks and the same is attributable to the increased participation of short sellers in the market. Grullon, Michenaud, and Weston (2015) find that the stock prices decrease for the Pilot firms and the smaller firms react by reducing the number of equity issues. Chen, Da, and Huang (2019) find that Net Arbitrage Trade (NAT) has stronger predictability for the non-Pilot stocks, which faced higher short-sale constraints.

Secondly, our work is strongly related to papers that have investigated how Regulation SHO has impacted firm behaviour. For instance, Li and Zhang (2015) find that the management forecast precision for pilot firms for bad news, defined as the negative width of the management forecast, decreases for the Pilot firms. Gong (2020) documents that firms decrease their book leverage in response to the short selling threat. Clinch, Li, and Zhang (2019) find that compared to the non-Pilot firms, the Pilot firms have greater and more timely bad news forecasts and earnings news. In this context, the paper demonstrates that Regulation SHO has led to a greater decline in large jumps for firms that are less conservative, implying that increased short-selling has resulted in a decline in their jump intensity.

Finally, the paper is also related to the research on the behaviour of the jump components of volatility. Several papers examine the behaviour of jumps in the market. Bollerslev, Li, and Zhao (2017) find that a measure of good minus bad jumps (RSJ) is priced negatively by the market. Bollerslev, Li, and Todorov (2016) find that "rough-βs", which are sensitivity of a stock's returns to market jumps, are priced significantly by the market. The jump component of volatility is offered as the explanation for large credit spreads in investment grade bonds (eg. Tauchen & Zhou, 2011; Zhou, 2001). Patton and Sheppard (2015) find that past negative (positive) stock price jumps predict higher (lower) volatility of stock returns. Kim, Oh, and Brooks (1994) find that the jump risks of stocks are non-diversifiable and hence are priced in the market as idiosyncratic risks. Our paper demonstrates that relaxation of the short-sale constraints is strongly associated with a decline in the large jumps significantly and a simultaneous increase in small jumps.

The remainder of the paper is organised as follows. Section 2 details the conceptual background and lays down our key hypotheses. Section 3 describes the methodology and data. Section 4 discusses our key findings and their implication and Section 5 presents the robustness of our results. Section 6 concludes the paper with the key insights obtained from the research.

2. Conceptual background and hypotheses

Regulation SHO has been employed by various studies related to short-sale constraints. The feature that makes it very attractive in a difference-in-differences setup is the random allocation of stocks to the relaxed short sale constraints regime. Diether et al. (2009) evaluate the impact of the regulation on the market quality of the pilot stocks and their daily volatility. Chu et al. (2017) show that certain anomalies that may be attributed to short sale constraints are reduced for pilot stocks during the pilot period. Boehmer, Jones, and Zhang (2020) use the end of the pilot program to show that when the constraints were relaxed for all stocks, short sellers became aggressive even in the pilot stocks.

When the stocks are short-sales constrained the stock prices are characterised by significant jumps. Accordingly, Das (2002) finds that if the Poisson jump process is incorporated in the short rates, they explain surprise US Fed interventions better than plain Gaussian models. Andersen, Benzoni, and Lund (2002) use jump-diffusion models and stochastic volatility to explain the skewness of S&P 500 returns, which were separately studied before this. They show that jumps and stochastic volatility are an integral part of the index price process.Maheu and McCurdy (2004) find that the unusual component of news causes jumps in stock prices. The impact of surprise macroeconomic announcement on the jump volatility has been documented in literature (eg. Bomfim (2003), Rangel (2011)). Comparing the impact of good news and bad news on bond price jumps, Beber and Brandt (2010) find that in good (bad) times, bad (good) macroeconomic news causes a larger impact to jump volatility of bonds. On similar lines, Evans (2011) finds that intra-day jumps are associated with macroeconomic news. Overall, the literature documents that short selling constraints lead to overpricing of stocks, mostly due to the non-trading of stocks with negative information which results in price jumps.

The recent research has developed techniques to decompose volatility into jumps both large and small as well as positive and negative, which enables us to examine the impact of short sale constraints on these components separately. The decomposition of volatility into jumps has been used in various strands of literature. Patton and Sheppard (2015) employ it examine the forecasting power of positive and negative semi-variance for realised variance. Segal, Shaliastovich, and Yaron (2015) show that positive (negative) uncertainty predicts an increase (decrease) in macroeconomic activity. Duong and Swanson (2015), working with large and small jumps show that it is small jumps that help in the prediction of future volatility using a HAR model, instead of large jumps. Baruník, Kočenda, and Vácha (2016) use the concept of derived networks to show that there is an asymmetry in volatility spillover in the positive and negative semi-variance networks. In asset pricing, Ang, Chen, and Xing (2006) show that it is the downside beta that is relevant for the pricing of assets. Bollerslev et al. (2017) employ the good minus bad jumps from high-frequency return data to estimate its impact on the cross-section of stock returns. They observe that this measure negatively predicts future stock returns. More recently Yu, Mizrach, and Swanson (2019) and Guo, Wang, and Zhou (2014) show that positive (negative) components of volatility have an negative (positive) risk premium. Alexeev, Urga, and Yao (2019) show that if diversification of extreme risk is the objective, then it takes more stocks to diversify extreme negative risk compared to diversifying extreme positive risk.

Given the evidence that surprise information enters the market in the form of jumps (Bomfim, 2003; Das, 2002), we expect that when market participants are short sale constrained, negative private news will be difficult to be incorporated into the prices. Instead, it will assume the form of a shock to the market when it is revealed, leading to large jumps in stock returns. On the contrary, when short-sale constraints are relaxed, the negative news will impact the prices more regularly and hence there will be fewer large jumps. Therefore we hypothesize that:

Hypothesis 1 *Positive and negative large (small) jump intensity should be lower (higher) in the post-announcement period.*

Literature has documented that the pilot SHO program had a random selection of stocks (He and Tian (2015) etc.). Hence, the short sale constraints were relaxed for a random set of stocks, while they remained in place for the non-pilot stocks, for the pilot period of approximately three years. Therefore, in the pilot period we expect the large (small) jump intensity to be lower (higher) for the pilot stocks relative to the non-pilot stocks. This leads to our second hypothesis:

Hypothesis 2 *During the pilot period, large (small) jump intensity should be lower (higher) for the pilot stocks compared to the non-pilot stocks.*

It is also documented that short sale constraints are greater for the smaller stocks (D'avolio, 2002; Jones & Lamont, 2002). Therefore, we expect that the impact of relaxing short sale constraints will be greater for the smaller stocks. Hence we should observe a greater decrease (increase) in the large (small) jump intensity for the smaller stocks. This leads us to our third hypothesis:

Hypothesis 3 *In the pilot period the decrease (increase) in large (small) jump intensity should be higher for the smaller pilot stocks.*

3. Data and methodology

Our data begins from January 1998 and ends in December 2018. The period from January 1998 until August 2007 is taken as the pilot period for the DiD analysis. We download the daily price data from CRSP provided by WRDS. We exclude a firm on a day if the stock price is less than \$1 or if it is more than \$1000. We also exclude financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4999. We consider only observations with non-missing closing price data. Daily returns for a firm for day are calculated using the formula below:

$$r_{i,t} = log(P_2/P_1) \tag{1}$$

where P_2 is the closing price on the return calculation day and P_1 is the opening price on the same day. In case the opening price on a day is not available, we consider the closing price on the prior day as P_1. We then use the returns data to calculate the components of variance, as described in Section 3.1. As our unit of observation is a firm-month, we exclude any firm-month with less than 12 return observations.

The annual data on total assets is downloaded from Compustat, provided by WRDS. As the data for total assets are available only at an annual frequency, it is regarded as the same for a firm over the 12 months of a year. In our final sample, we are left with 231,717 firm-month observations and they correspond to 3,432 unique firms.

For the idiosyncratic volatility estimation, we follow the market model. For each year, for each firm, we run the model as below:

$$R_{i,t} = \beta_0 + \beta_1 \times MarketRet_t + \epsilon_{i,t} \tag{2}$$

where $R_{i,t}$ is the returns of stock for a day and $MarketRet$ is the market factor for the day t, taken from Ken French's website. We run a separate regression model for each firm, each year to accommodate time variation in market risk. We take the $\epsilon_{i,t}$ as the residual return for the day t and use it for the calculation of volatility and its components.

With the residual returns, we calculate the monthly idiosyncratic volatility ($IVOL$) for each stock and decompose the same into its components, as described in Section 3.1 below. We work with $IVOL$ to remove the impact of market-wide news on stock returns and focus only on how firm-specific news impacts components of volatility.

3.1. Calculation of components of variance

We employ the recently developed techniques to extract five components of volatility, a.) positive large jump b.)negative large jump c.) positive small jump d.) negative small jump and e.) a continuous component (called Integrated volatility or IV).

Recent literature has proposed ways to extract signed large and small jumps from high frequency returns data (Barndorff-Nielsen et al., 2008; Yu et al., 2019). The details of the variables and the way they are derived from the high frequency returns data are given below. We follow the approach of Yu et al. (2019). In principle, they decompose the total variance into a continuous part, signed small jumps, and signed large jumps. They first use tri-power variation, defined below, to derive the continuous part of the volatility

$$IV_t = \sum_{i=3}^{M} |r_i, t||r_i - 1, t||r_i - 2, t| * K \tag{3}$$

Where, M = Number of observations in a day or period, $r_{i,t}$ the return at the interval i of the period t, for the security in consideration and K is the $2/3^{rd}$ absolute moment of the standard normal distribution

We use one month as a period, and a day as an interval within a month in our calculations of volatility components.

Working under the assumption that the total volatility consists of the jump volatility and the continuous volatility, the Realised Jump Variation (RJV) is computed using the formula below,

$$RVJ_t = max(RV_t - IV_t, 0) \tag{4}$$

where,

$$RV_t = \sum_{n=1}^{M} r_t^2 \tag{5}$$

is the measure of the realised variance.

Now we separate large jumps from small jumps based on a threshold "g" using the equation below

$$RVLJ_{g,t} = min(RVJ_t, \sum_{n=1}^{n} r_{i,t}^2 * I_{|r_{i,t}|>g}) \tag{6}$$

where i is the indicator variable representing absolute return greater than g. From the total jump, as given in Equation 4, the small jump may be found by reducing the large jump, as given in Equation 6.

Subsequently, the realised semi-variance is computed by appending Equation 5 with an indicator variable to represent the sign of the return.

$$RVP_t = \sum_{n=1}^{M} r_t^2 * I_{r_t>0} \tag{7}$$

We use the IV to proxy the continuous part, as given in Equation 3. Then we deduct half the IV from the realised positive (negative) semi-variance to obtain the realised positive jump variation ($RVJP_t$) and the realised negative jump variation ($RVJN_t$)), as given below:

$$RVJP_t = RVP_t - 1/2 * IV \tag{8}$$

Finally, to calculate the large signed jump variation from the two (+ and-) jump measures as calculated above, we use the following equation:

$$RVLJP_t = min\left(RVJP_t, \sum_{n=1}^{n} r_{i,t}^2 * I_{\{r_{i,t}>g\}}\right) \tag{9}$$

Where g is the defined threshold separating small jumps from large jumps. Similarly, we calculate the $RVLJN_t$, the negative large jump variation. We then estimate the large jump variation from the total signed jump variations of either sign, to find the signed small jump variation.

$$RVSJP_t = RVJP_t - RVLJP_t \tag{10}$$

$RVSJN_t$ is calculated in an analogous manner.

Finally, we calculate the intensity of jumps by taking the ratio of the realised jump component with the total realised volatility for the month. These four jump intensities are the dependent variables in our empirical analysis.

$$NLJ_t = RVLJN_t / RVOL_t \tag{11}$$

$$PLJ_t = RVLJP_t / RVOL_t \tag{12}$$

$$NSJ_t = RVSJN_t / RVOL_t \tag{13}$$

$$PSJ_t = RVSJP_t / RVOL_t \tag{14}$$

To determine the threshold for large jumps, we use the following method. We pool all the observations of daily returns in our sample for all firms and find the 75th percentile break-point of returns sorted by size. For the baseline analysis, all returns that are larger than this break-point, are considered large (about 3% in our data). As a robustness check, we use two other thresholds, 70th and 80th percentile breakpoints of pooled daily returns (2.5% and 3.5% in our data, respectively).

3.2. Empirical Specification

In the pilot phase, roughly 1000 listed stocks were selected and the uptick rule was relaxed for these stocks, without affecting the remaining listed stocks. Prior research has documented that in regulation SHO, selection of pilot stocks was indeed random (eg., Diether et al., 2009; He & Tian, 2015). Studies have used the pilot SHO program and the inherent DiD approach that the program enables. For instance, Chu et al. (2017) use the fact that the selection of stocks for the pilot program was random in a DiD set up to show that certain anomalies, attributable to short selling constraints, become weaker for the pilot stocks, during the pilot period. Since our study is closely related to theirs, we use a similar setup to show that information flow indeed impacted the jump intensities of the pilot stocks differently. We include the size of the firm as a control variable. As has been documented in the literature, smaller stocks are harder to short (D'avolio, 2002;

Jones & Lamont, 2002). Controlling for firm size, therefore, will enable us to isolate the impact of regulation SHO.

In our first specification, to test Hypothesis 1, we focus on all the firms in our sample. We do this to examine our hypothesis that in the Post-SHO period, the NLJ (NSJ) will decrease (increase) for all stocks. We use the specification below:

$$Var_{i,t} = \beta_0 + \beta_1 \times SHO_t + \beta_2 \times log(Asset)_{i,t} + \epsilon_{i,t} \tag{15}$$

where SHO_t is a dummy variable that takes 1 in all months after July 2004, $log(Asset)_{i,t}$ is the log of the assets of a firm for the month t.

To test the impact of relaxing short-selling constraints on the pilot stocks in the pilot period (Hypothesis 2), we use the baseline difference in differences specification below:

$$\begin{aligned} Var_{i,t} = \beta_0 &+ \beta_1 \times PilotFirm_i + \beta_2 \times SHO_t + \beta_3 \times PilotFirm_i \times SHO_t \\ &+ \beta_4 \times log(Asset)_{i,t} + \epsilon_{i,t} \end{aligned} \tag{16}$$

$Var_{i,t}$ is the measure of the jump, either NLJ, PLJ, NSJ, or PSJ for a firm i in month t, $PilotFirm_i$ is a dummy variable that takes the value of 1 for all Pilot firms and 0 otherwise, $log(Asset)_{i,t}$ is the log of total assets and SHO_t is a dummy which takes 1 for al months from the announcement of the program to end of the pilot period. β_3, the coefficient of the interaction of the $PilotFirm_i$ and SHO_t is expected to be negative (positive) for large (small) jumps (both positive and negative) and significant.

In both our specifications above, we run a regression without any controls and another with year and firm fixed-effects to take care of any time-invariant firm-specific characteristics and time-variant system-wide shock, impacting all stocks alike.

To examine Hypothesis 3 of the impact of firm size on the change in large and small jumps in response to the Pilot Program, we place both the Pilot and non Pilot firm-months together in a Diff-in-Diff-in-Diff(DiDiD) setup. A DiDiD is a triple difference estimator to examine the differential impact of firm size on the primary effect of easing short sale constraints on volatility components. We estimate the equation:

$$
\begin{aligned}
var_{i,t} = {} & \beta_0 + \beta_1 \times PilotFirm_i + \beta_2 \times log(Asset)_{i,t} + \beta_3 \times PilotFirm_i \times log(Asset)_{i,t} \\
& + \beta_4 \times SHO_t + \beta_5 \times SHO_t \times PilotFirm_i + \beta_6 \times SHO_t \times log(Asset)_{i,t} \\
& + \beta_7 \times SHO_t \times PilotFirm_i \times log(Asset)_{i,t} + \epsilon_{i,t}
\end{aligned}
\tag{17}
$$

where SHO_t is a dummy taking 1 for the Pilot period and $SHO_t \times PilotFirm_i \times log(Asset)_{i,t}$ is the triple interaction. We expect β_7 to be positive (negative) for large (small) jumps.

4. Findings and discussion

4.1. Univariate analysis

We present the summary statistics of the jump components of volatility in Table 2. Panel A shows the difference in the realised NLJ in the pre-Announcement and post-Announcement periods and Panel B shows the analogous difference for PLJ. NLJ (PLJ) reduces in the post-announcement period by about 4% (4.8%), which is statistically significant. More importantly, in the Pilot period, the difference in the realised NLJ (PLJ) of the Pilot stocks and the non-Pilot stocks is about 3.5% (3.6%). The pilot stocks realise a statistically significant lower proportion of large jumps. The summary statistics for small jumps mirror the finding for the large jumps. As panel C shows, the NSJ in the post-announcement period is significantly lower. Similarly, the NSJ for the Pilot stocks is significantly higher during the pilot period. The difference between the Pilot and non-Pilot stocks is also plotted in Figure 1. As the figure shows, the groups are significantly different in the realised jumps, with large jumps being lower for the Pilot stocks and small jumps being higher.

4.2. Parallel trends

We examine if the Pilot and non-Pilot stocks were different in terms of their jump intensities before the regulation. If that were the case, it is hard to attribute the difference in their jump intensities to the Pilot program. Hence, estimate the equation below with each of the jump intensities as the dependent variable:

$$var_{i,t} = \beta_0 + \beta_1 \times year + \beta_2 \times year \times PilotFirm + \epsilon_{i,t} \quad (18)$$

where *year* captures the observation year. We expect that in the post-announcement years, the coefficient β_2 is significantly negative (positive) for the large (small) jumps. We plot the coefficient in Figures 2, 3, 4 and 5 for NLJ, PLJ, NSJ and PSJ respectively. Since the effect we describe is likely to be driven by smaller firms, as evidenced by the main results, we show the trends separately for firms that are above and below median asset size ($log(Asset)$) observations and additionally for the smallest 25% and 10% firms by assets. The top panel shows all firm-month observations, the middle panels show observations above and below median asset values and the last panel shows the smallest 25% and 10% of the observations. Consider the Figure 2 for NLJ. It is not obvious that the trends are parallel when all observations are pooled or in the above median asset size observations, however, there is a drop in the year 2005 onward, the first full year after the announcement. In the subset of smaller firms, especially in the below-median firm size observations, the trends are parallel pre-2005 and then drop from that year onward. The same holds true for the smaller subset of observations as shown in the last panel. The results are qualitatively similar for PLJ (Figure 3 and mirror those of large jumps in Figures 4 - 5, for small jumps). Overall, we may conclude that the parallel trends assumption holds largely true for the main analysis.

4.3. Key findings from the DiD analysis

Table 3 presents the results of the examination of Hypothesis 1. The realised NLJ (PLJ) in the post-announcement period is lower by 2.5% (3.0%), as shown in columns (1) and (3) of the table. The difference increases marginally with the firm fixed effects and year fixed effects. In contrast, the realised NSJ (PSJ) is higher in the post-announcement period by 2.3% (2.3%). Hence there is evidence that the price-sensitive information, diffuses into the market more gradually in the post-announcement period. Hence, the findings support Hypothesis 1.

To examine the difference between the Pilot and the non-Pilot stocks in the Pilot period, we estimate Equation 16. We expect the Pilot stocks to realise incrementally lower (higher) large (small) jumps. The results are presented in Table 4. The coefficient of $SHO \times PilotFirm$ is significantly negative for the large jumps and positive for the small jumps. For instance, NLJ is lower by about 1.1% in the Pilot stocks compared to the non-Pilot stocks (as given in column (1)). Hence the large jump intensity for the pilot stocks is lower in the Pilot period, compared to the non-Pilot period. On the contrary, the small jump intensity for Pilot stocks in the Pilot period is higher, indicating smoother incorporation of information into the prices. For instance, the NSJ increases for the Pilot stocks in the Pilot period by about 1.8% (as given in column (5)). The observation holds for positive jumps as well. Overall, we find support for the hypothesis that relaxing of short sale constraints leads to a lower (higher) large(small) jump intensity.

We also estimate Equation 16 with the monthly total realised variance ($IVOL$ as defined in Equation 4) as the explained variable to examine the impact that the Pilot program had on the idiosyncratic variance. As is shown in the last two columns of Table 4, the $IVOL$ for the Pilot stocks is significantly higher compared to the non-Pilot stocks. Diether et al. (2009) report unchanged volatility at the daily level, though in a subset of smaller stocks, they find increased volatility among Pilot stocks. Our findings are in line with theirs, but we work with $IVOL$ as we are interested in the incorporation of firm-specific price-sensitive information into prices. Hence, despite the increase in overall $IVOL$, the large (small) jump intensity decreases (increases), indicating a smoother flow of stock-specific information into prices.

Finally, we examine the hypothesis that the change in jump intensities would be larger for smaller stocks, possibly due to the steeper short-selling constraints faced by such stocks (Hypothesis 3). Hence a regulatory intervention that eases the short-selling constraints for a random group of stocks, should benefit the smaller firms to a greater degree. We estimate the specification as shown in Equation 17 and present the results in Table 5. As hypothesised, the decrease in large jumps is smaller for larger firms. For instance, a 1% increase in asset size lowers the drop in NLJ by about 0.5%, which is significant at the 10% level (column 1). A comparable decreased drop is seen in PLJ, which is significant at the 5% level (column 2). In contrast to the lower drop in large jumps, the small jumps increase by a smaller amount for larger firms. For instance, for a 1% increase in asset size, the gain in NSJ is lower by 0.06% (column 3). Overall, we find evidence that the regulatory change impacted the price-sensitive information flow for the smaller firms, to a higher degree.

4.4. Managerial action channel associated with the impact of Regulation SHO on large jumps

In this section, we examine the likely role of increased accounting conservatism of firms on the decline in the large jumps associated with the relaxation of arbitrage constraints. We measure the accounting conservatism of a firm by their $CScore$ and $Gscore$, following Deng et al. (2020)[3], using data for FY 2003. We select year 2003 because it is the year immediately prior to the introduction of the regulation. For the analysis, we define two variables, $CScoreHigh$ and $GScoreHigh$. $CScoreHigh$ is a dummy variable that takes the value 1 for all observations that have $CScore$ value above the median. $GScoreHigh$ is an analogously defined dummy variable. A high $GScore$ indicates the tendency of a firm to selectively report good news and therefore, it is reflective of opportunistic reporting by firms. Conversely a high $CScore$ indicates the tendency to be conservative in accounting reports. Therefore, we expect a firm with a high $GScore$ to reflect a greater decline in large jumps as a result of easing of arbitrage constraints due to Regulation SHO. Conversely, we expect the stock of a firm with a high $CScore$ to reflect a smaller decline in their large jumps.

The results of the estimation of Equation 17 are presented in Table 9. The coefficient of $SHO \times PilotFirm \times Characteristic$ is positive and significant in both columns 1 and 2, indicating a smaller decline in the large jumps for firms with a high $CScore$. Conversely, the correspoinding decline is greater for firms with a higher $GScore$, as shown in columns 5 and 6. The results for small jumps mirror those for the large volatility jumps. Taken together, the results indicate that management of firms with lower accounting conservatism contributes to the increased flow of negative information. Hence,

[3]We refer the reader to Deng et al. (2020) for the details of the methodology.

it is likely that the easing of the arbitrage constraints by Regulation SHO, impacted the less conservative firms to a greater degree.

5. Robustness tests

5.1. Placebo Pilot period

We examine if the difference between the large and small jumps of Pilot and non-Pilot stocks exists in sample periods that did not overlap the Pilot program window. We do this analysis for two sub-samples, one before the announcement of the program and another after the announcement. As the first sub-sample, we select the period from January 1998 to June 2003 and within this period, January 2000 to June 2003 as the placebo Pilot period. We deliberately stop at a point about a year before the announcement to control for any rumours in the market. As the second sub-sample, we select the period from January 2010 to December 2017 and within this sample, January 2014 to December 2017 as the placebo Pilot period. Again, deliberately avoid the crisis months as this was a period of extreme market movements. We estimate the Equation 16 on these sub-samples any difference in the jump characteristics of these two sets of stocks. The results are presented in Table 6. The coefficient $SHO \times PilotFirm$ is not significant for any of the four components of jumps, in either of the sub-samples. Hence, in the placebo periods, the effect of lower (higher) large (small) jump intensity, documented above, does not exist. This gives support to our hypothesis that the difference in the jump characteristics was on account of the selective relaxation of the short sale constraints during the Pilot period.

5.2. Alternative jump thresholds

Our selection of the 75th percentile break-point for the absolute return distribution in the period is somewhat arbitrary and data-driven. Hence, we examine if altering this threshold makes a difference to our main results. For this purpose, we use alternative thresholds at the 70th and the 80th percentile breakpoints of the absolute return distribution. We select a reasonably high threshold but are careful not to set it so high that the number of observations in the smaller sample is too low to influence our results. We then estimate Equation 16 and show the results in Table 7. The results and their significance are qualitatively the same as our main results. Hence, the selection of alternative jump thresholds makes little difference to our main result.

5.3. Smaller window around the announcement

We examine the robustness of Hypothesis 1 to the selection of the window around the announcement of the program. As the information efficiency of prices has improved with the increased rate of information flow, over a period of 20 years that we take, it is likely that the large jumps decrease for reasons unrelated to the Pilot program. Hence we select a smaller window from January 2002 to December 2005 and estimate Equation 18 to examine the validity of Hypothesis 1. The results are shown in Table 8. Again, the key results are qualitatively the same as described in the baseline analysis. For instance, in the post-announcement period, the NLJ decreases by about 3.2% in this sample, compared to about 3.6% in the main sample (Table 3, column 2). Hence, the claim that it was the Pilot program that was responsible for the drop, appears to be valid.

5.4. Alternative proxies for constraints to arbitrage

In our baseline analysis, we use the firm size as a proxy for constraints to arbitrage. Literature has proposed several other proxies for the same. For instance, a higher proportion of institutional holding and a higher concentration of holding is associated with lower constraints to arbitrage due to easier availability of lend-able shares (Nagel, 2005). In a similar vein, less liquid stocks are more likely to face binding arbitrage constraints (D'avolio, 2002) and therefore, the regulation is likely to impact their information efficiency to a greater degree.

We therefore employ both institutional ownership and Amihud's (Amihud, 2002) illiquidity as proxies for the arbitrage constraints faced by the market in the stock of a firm. The results are presented in Table 5, columns 5-12.

In columns 5-8, we employ $HighInstitutionalOwnership$ as a proxy for the arbitrage constraints. The variable takes the value 1, if the institutional ownership of the stock of a firm is above the median institutional ownership in the sample, for the year 2003. The coefficient of $SHO \times PilotFirm \times Characteristic$ is positive and significant in columns 5 and 6. We therefore conclude that firms with higher institutional ownership, which likely face lower arbitrage constraints, have a lower decrease in the large jumps as a result of the regulation. The result for small jumps mirrors that for the large jumps.

Analogously, in columns 9-12, we employ Amihud's illiquidity as a measure of arbitrage constraints. Amihud's illiquidity is estimated for the year 2003, using daily stock returns and volume. The coefficient of $SHO \times PilotFirm \times Characteristic$ is negative and significant in columns 9 and 10, indicating that firms with more illiquid stock had a larger decline in their large jumps. The results for small jumps in columns 11 and 12 mirror those for large jumps. We therefore find that for alternative proxies of arbitrage constraints, our result that the large jumps of firms with greater arbitrage constraints declined to a greater degree, holds.

6. Conclusion

In this paper, we examine the impact of relaxation of short sale constraints on the components of volatility by employing some of the recently developed econometric techniques to decompose total volatility into its components. We find that the relaxation of the constraints through the Pilot SHO program leads to a significant decrease (increase) in large (small) jumps. We argue that the decline in the large jumps and the increase in the small jumps are observed on account of a more unhindered flow of negative information into the market, with increased participation of short sellers. It allows the pessimistic views to be more readily incorporated into prices, leading to a more smooth incorporation of price-sensitive information. The results hold for alternative definition of large jump thresholds, shorter event window around the Pilot program and alternative proxies to reflect firm-level arbitrage constraints.

We offer an explanation for the observed increase in the large jumps by linking it with the level of accounting conservatism of firms. Particularly, we examine whether the decline in the large jumps is associated with the disclosure practice of firms immediately prior to the easing of short-sale constraints. We find that the decrease in the large jumps is more remarkable for firms with a lower score on accounting conservatism. While our research has brought out that easing of the short-sale constraints through the Pilot program has led to a decline in the intensity of large jumps, it could be an outcome of the change in the information environment of firms. More timely and quality disclosures by firms during the SHO period are also likely to contribute to the difference in the intensity of jumps observed in the paper.

Our results have implications for policymakers and traders. As we show, large jumps are reduced as the short-sale constraints are relaxed. Hence the jump risk is lower when short sales are allowed. As Yu et al. (2019) show, the risk premium for jumps is positive or the market seeks compensation for taking the risk of large jumps. Hence a policy that allows relaxing short selling constraints would result lower risk premium for the stocks.

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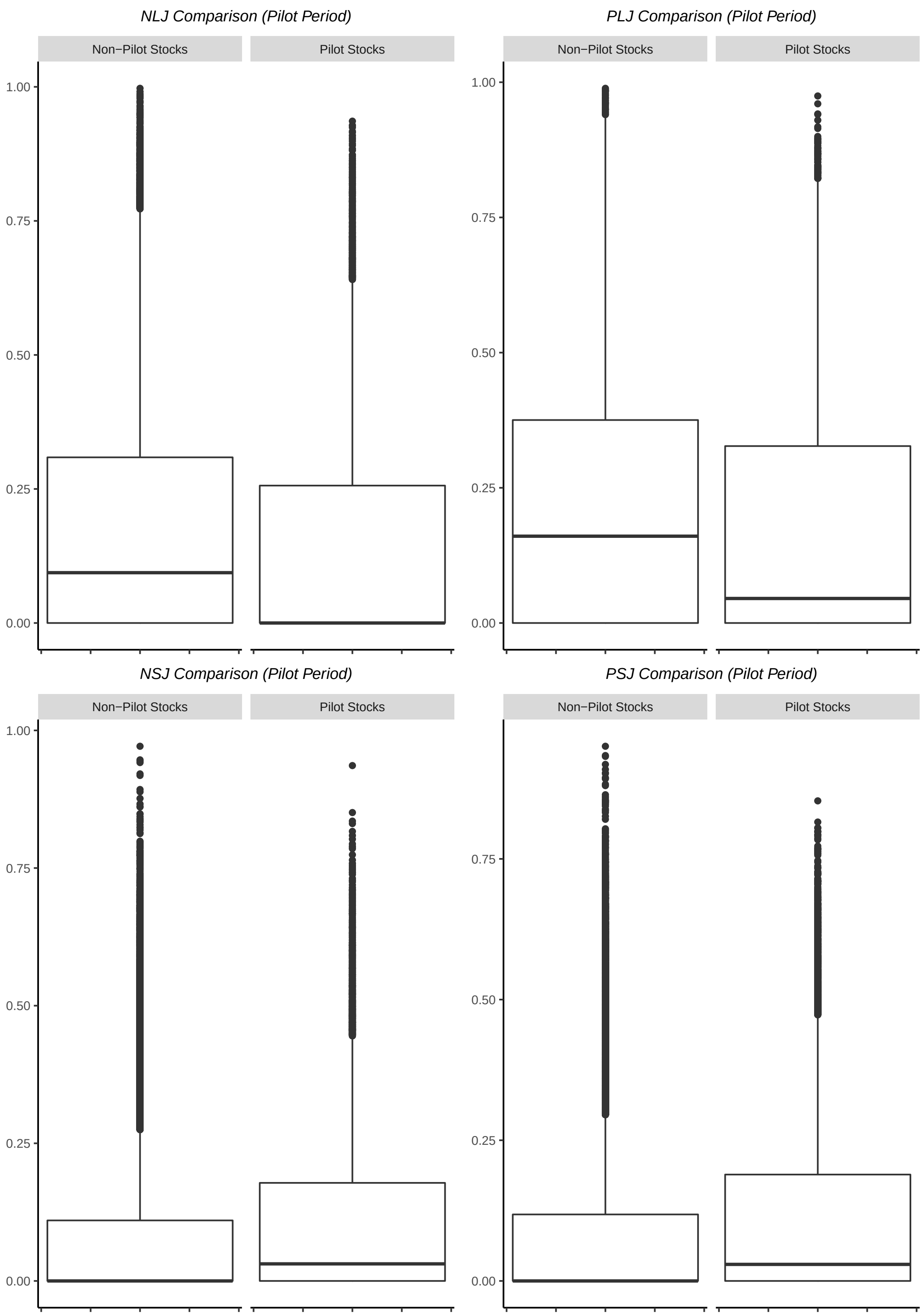
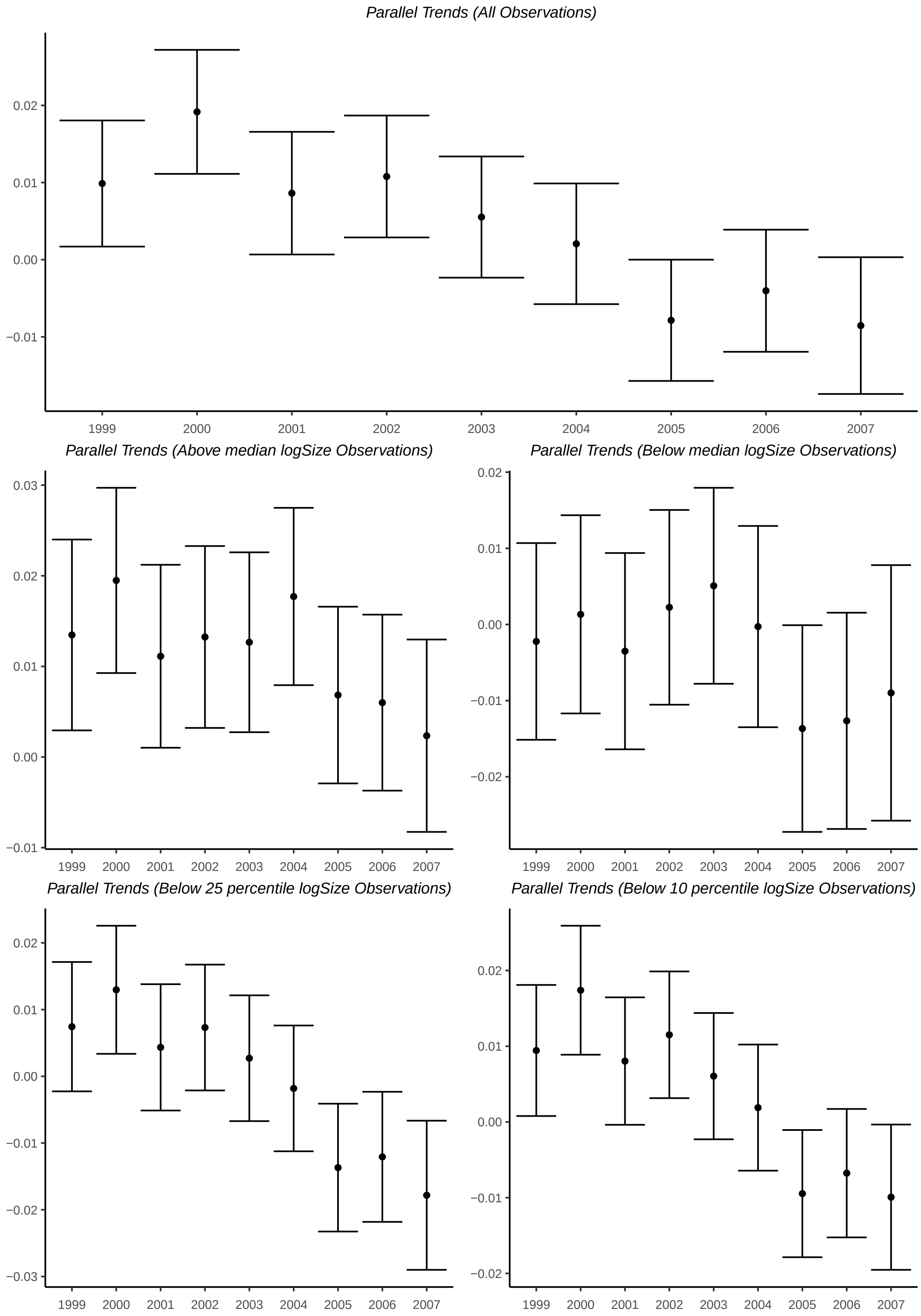
Figure 1: Jumps Comparison in the Pilot Period



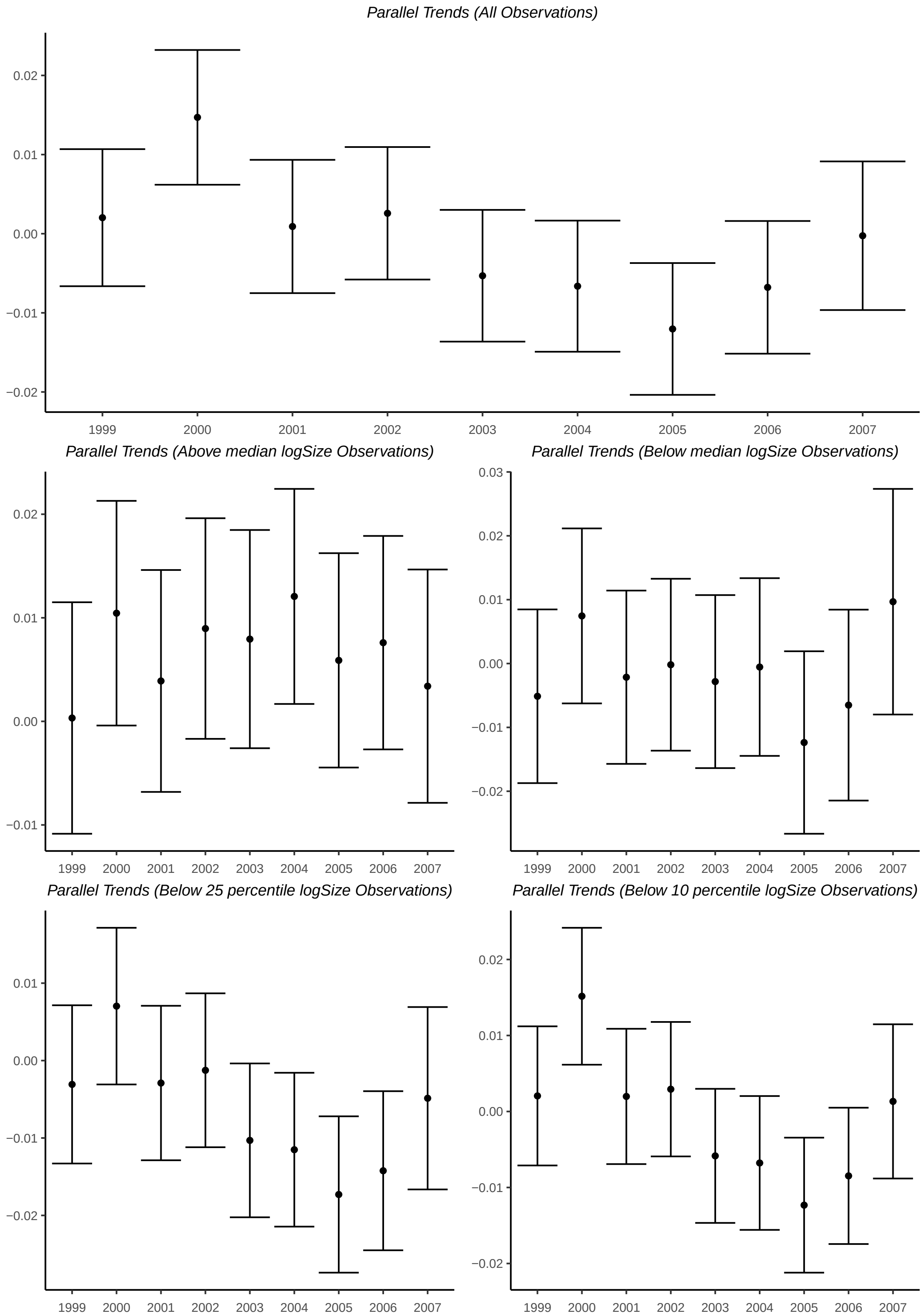
This figure compares the distribution of NLJ, PLJ, NSJ and PSJ in the Pilot Period between the Pilot stocks and non-Pilot stocks

Figure 2: Parallel Trends - NLJ



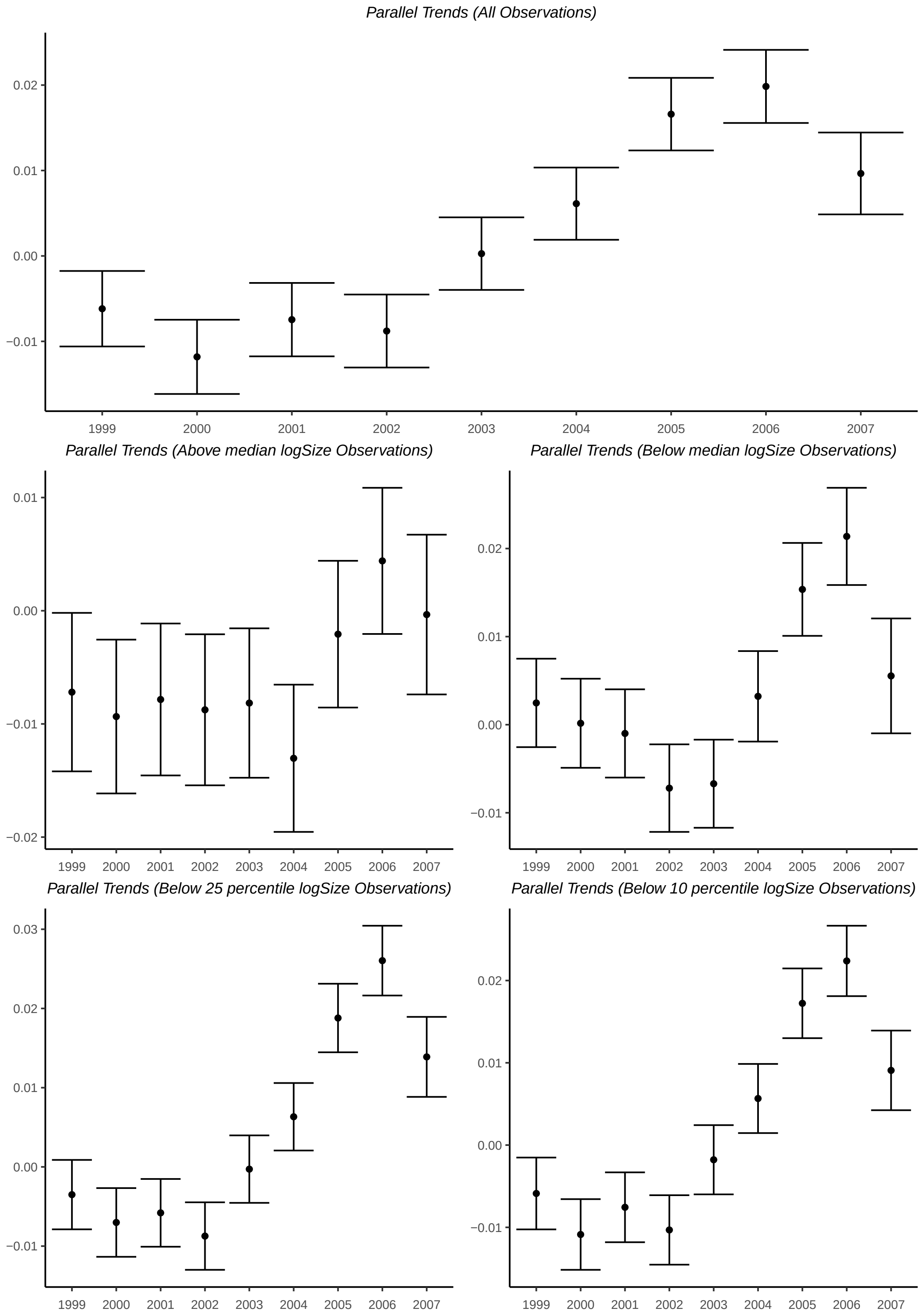
The figure tests the parallel trends assumption for NLJ

Figure 3: Parallel Trends - PLJ



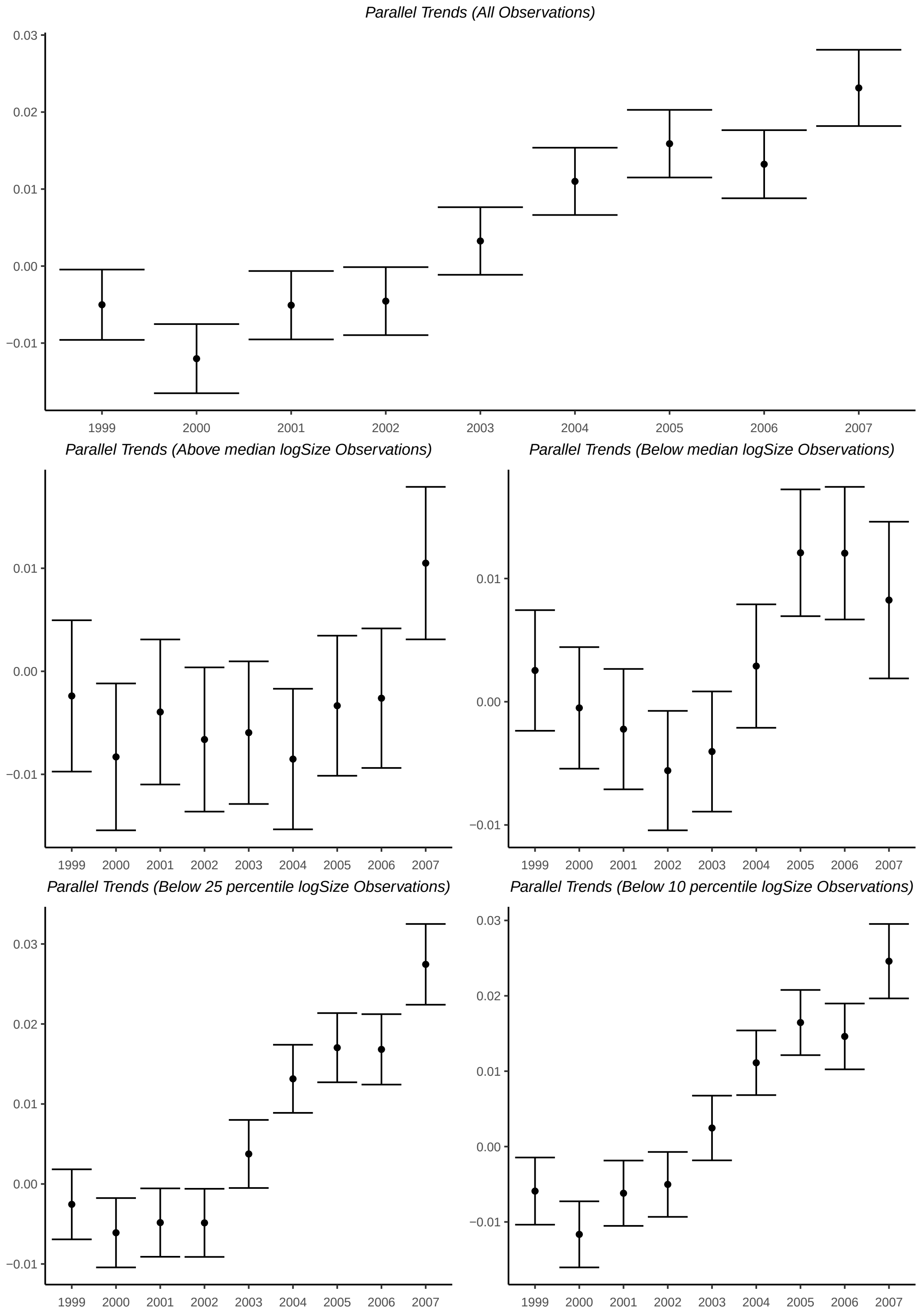
The figure tests the parallel trends assumption for PLJ

Figure 4: Parallel Trends - NSJ



The figure tests the parallel trends assumption for NSJ

Figure 5: Parallel Trends - PSJ



The figure tests the parallel trends assumption for PSJ

Table 1: Variable definitions and data sources

Variable	Definition and construction	Data source
NLJ	Negative large jump volatility of daily stock returns for a stock over a month divided by the realised idiosyncratic volatility of daily returns for the same stock over the same month.	WRDS
PLJ	Positive large jump volatility of daily stock returns for a stock over a month divided by the realised idiosyncratic volatility of daily returns for the same stock over the same month.	WRDS
NSJ	Negative small jump volatility of daily stock returns for a stock over a month divided by the realised idiosyncratic volatility of daily returns for the same stock over the same month.	WRDS
PSJ	Positive small jump volatility of daily stock returns for a stock over a month divided by the realised idiosyncratic volatility of daily returns for the same stock over the same month.	WRDS
$log(Asset)$	Natural log of the book value of assets as of the last annual report for a firm.	WRDS
$SizeLarge$	A dummy variable that takes the value 1 for all observations that have an above median value of $log(Asset)$ for the year 2003.	WRDS
$GScore$	The "Good news score" of a firm for the FY 2003. It is calculated employing the methodology detailed in Deng et al. (2020).	WRDS
$CScore$	The "Conservatism score" of a firm for the FY 2003. It is calculated employing the methodology detailed in Deng et al. (2020).	WRDS
$GScoreHigh$	A dummy variable that takes the value 1 for all observations that have an above median $GScore$.	WRDS
$CScoreHigh$	A dummy variable that takes the value 1 for all observations that have an above median $CScore$.	WRDS
$IlliquidityHigh$	A dummy variable that takes the value 1 for all observations that have an above median Amihud's illiquidity (Amihud, 2002) estimated for the year 2003.	WRDS
$InstitutionalOwnershipHigh$	A dummy variable that takes the value 1 for all observations that have an above median institutional ownership for the year 2003.	WRDS

Table 2: Summary statistics of key variables

Variable	Pre-Pilot Period	Pilot Period		Post-Pilot Period	Pre minus Post	t-stat.	Diff.	t-stat.
		Non-Pilot Stocks	Pilot-Stocks					
Panel A: NLJ								
Mean	0.236	0.174	0.139	0.196	0.040	71.355	0.035	19.619
SD	0.216	0.207	0.194	0.210				
Median	0.199	0.094	0.000	0.146				
Panel B: PLJ								
Mean	0.268	0.212	0.175	0.220	0.048	125.349	0.036	31.029
SD	0.225	0.226	0.215	0.220				
Median	0.245	0.161	0.045	0.181				
Panel C: NSJ								
0.064	-0.037	-61.727	-0.031	-20.729				
SD	0.086	0.135	0.151	0.126				
Median	0.000	0.000	0.031	0.000				
Panel D: PSJ								
Mean	0.026	0.084	0.114	0.063	-0.037	-121.826	-0.031	-24.159
SD	0.086	0.144	0.158	0.127				
Median	0.000	0.000	0.029	0.000				
Panel E: Other Variables	Mean	SD	Median					
log(Asset)	2.737	0.865	2.702					
Prop_Inst	0.529	0.291	0.551					
HHI_Inst	0.139	0.169	0.073					

Notes: SD stands for standard deviation. All variable definitions are available in Table 1.

Table 3: Volatility components: Impact of short-selling rule on account of Pilot program

Variable	Large jumps				Small jumps			
	NLJ		*PLJ*		*NSJ*		*PSJ*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SHO	-0.025***	-0.033***	-0.037***	-0.038***	0.027***	0.032***	0.026***	0.028***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
log(Asset)	-0.044***	-0.041***	-0.052***	-0.062***	0.039***	0.044***	0.040***	0.051***
	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)
Constant	0.345***	0.342***	0.400***	0.428***	-0.070***	-0.088***	-0.073***	-0.105***
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)
N	437,947	437,944	437,947	437,944	437947	437944	437947	437944
R^2	0.04	0.063	0.055	0.078	0.103	0.202	0.107	0.201
Firm Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes

Notes: *SHO* is a dummy variable that takes value of 1 for all the months in the Pilot-period. All other variables are defined in Table 1. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 4: DiD analysis of the impact of Pilot program on $IVOL$ components of Pilot stocks

Variable	Large Jumps				Small Jumps				Total	
	NLJ		PLJ		NSJ		PSJ		RV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PilotFirm	-0.007***		-0.008***		-0.001		0		-0.006***	
	(0.001)		(0.001)		(0.001)		(0.001)		(0.000)	
SHO	-0.058***	0.020***	-0.049***	0.020***	0.051***	-0.011***	0.045***	-0.014***	-0.022***	0
	(0.001)	(0.004)	(0.001)	(0.005)	(0.001)	(0.003)	(0.001)	(0.004)	(0.000)	(0.000)
$SHO \times PilotFirm$	-0.017***	-0.014***	-0.010***	-0.007**	0.021***	0.019***	0.024***	0.017***	0.007***	0.004***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.000)
log(Asset)	-0.044***	-0.028***	-0.052***	-0.038***	0.038***	0.026***	0.034***	0.022***	-0.016***	-0.006***
	(0.001)	(0.003)	(0.001)	(0.003)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Constant	0.333***	0.272***	0.389***	0.333***	-0.055***	-0.011***	-0.044***	0.002	0.076***	0.044***
	(0.002)	(0.008)	(0.002)	(0.008)	(0.001)	(0.003)	(0.001)	(0.004)	(0.000)	(0.002)
No. of obs.	190,842	190,823	190,842	190,823	190,842	190,823	190,842	190,823	190,842	190,823
Adjusted R^2	0.052	0.079	0.053	0.082	0.121	0.218	0.104	0.236	0.119	0.286
Firm Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: All variables are defined in Table 1. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5: Impact of arbitrage constraints on change in jumps in response to Pilot program

Characterisitic	*SizeLarge*				*InstitutionalOwnershipHigh*				*IlliquidityHigh*			
Variable	Large Jumps		Small Jumps		Large Jumps		Small Jumps		Large Jumps		Small Jumps	
	NLJ	PLJ	NSJ	PSJ	NLJ	PLJ	NSJ	PSJ	NLJ	PLJ	NSJ	PSJ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$PilotFirm$	-0.014***	-0.018***	0.003**	0	-0.0247***	-0.0281***	0.0106***	0.0100***	-0.0035**	-0.0052***	0.0033***	0.0027***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
SHO	-0.054***	-0.041***	0.034***	0.031***	-0.0593***	-0.0517***	0.0437***	0.0395***	-0.0902***	-0.0907***	0.0996***	0.0872***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
$SHO \times PilotFirm$	-0.022***	-0.008*	0.018***	0.031***	-0.0295***	-0.0235***	0.0351***	0.0385***	-0.0034	0.0072*	-0.0027	0.0006
	(0.005)	(0.005)	(0.003)	(0.002)	(0.004)	(0.005)	(0.003)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)
$Characteristic$	-0.054***	-0.064***	0.038***	0.035***	-0.0414***	-0.0480***	0.0258***	0.0224***	0.0552***	0.0614***	-0.0325***	-0.0296***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$PilotFirm \times Characterisitic$	0.005	0.008***	0.003*	0.005***	0.0140***	0.0151***	-0.0027*	-0.0022	-0.0184***	-0.0172***	0.0047***	0.0041***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
$SHO \times Characteristic$	-0.031***	-0.047***	0.059***	0.047***	-0.0181***	-0.0203***	0.0355***	0.0286***	0.0341***	0.0491***	-0.0643***	-0.0554***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)
$SHO \times PilotFirm \times Characteristic$	0.016***	0.013**	-0.014***	-0.027***	0.0241***	0.0279***	-0.0327***	-0.0324***	-0.0116**	-0.0136**	0.0197***	0.0223***
	(0.006)	(0.006)	(0.003)	(0.003)	(0.006)	(0.006)	(0.003)	(0.003)	(0.006)	(0.006)	(0.003)	(0.003)
$Constant$	0.252***	0.292***	0.019***	0.021***	0.2455***	0.2846***	0.0249***	0.0264***	0.1944***	0.2260***	0.0563***	0.0550***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
No. of obs.	190,842	190,842	190,842	190,842	188807	188,807	188,807	188,807	169,151	169,151	169,151	169,151
Adjusted R^2	0.044	0.044	0.11	0.093	0.0339	0.0293	0.0762	0.0656	0.0458	0.0429	0.1031	0.0892

Notes: All variables are defined in Table 1. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 6: Robustness : Different placebo Pilot periods

Variable	Large Jumps		Small Jumps	
	NLJ	PLJ	NSJ	PSJ
	(1)	(2)	(3)	(4)
Panel A: Jan 1998 to Jun 2003 subsample - Pilot period - Jan 2000 to Jun 2003				
SHO × *PilotFirm*	0.002	0	-0.004**	-0.002
	(0.003)	(0.003)	(0.002)	(0.002)
No. of obs.	129155	129155	129155	129155
adjusted R^2	0.062	0.074	0.219	0.215
Panel B: Jan 2010 to Dec 2017 subsample - Pilot period - Jan 2014 to Dec 2017				
SHO × *PilotFirm*	0.002	0.003	0	-0.003
	(0.002)	(0.003)	(0.002)	(0.002)
No. of obs.	209,472	209,472	209,472	209,472
adjusted R^2	0.087	0.098	0.231	0.234

Notes: All variables are defined in Table 1. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 7: Robustness: Alternative thresholds for large jumps

Variable	Large Jumps		Small Jumps	
	NLJ	PLJ	NSJ	PSJ
	(1)	(2)	(3)	(4)
	Threshold - 70 Percentile			
SHO × PilotFirm	-0.012***	-0.006**	0.017***	0.016***
	(0.003)	(0.003)	(0.002)	(0.002)
No. of obs.	190823	190823	190823	190823
R^2	0.079	0.072	0.217	0.229
	Threshold - 80 Percentile			
SHO × PilotFirm	-0.011***	-0.005**	0.016***	0.015***
	(0.002)	(0.003)	(0.002)	(0.002)
No. of obs.	190,823	190,823	190,823	190,823
adjusted R^2	0.127	0.128	0.235	0.263
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Notes: All variables are defined in Table 1. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 8: Robustness: Pre-Post analysis with a shorter window

Variable	Large Jumps		Small Jumps	
	NLJ	*PLJ*	*NSJ*	*PSJ*
	(1)	(2)	(3)	(4)
SHO	-0.032***	-0.017***	0.022***	0.027***
	(0.002)	(0.002)	(0.001)	(0.001)
log(Asset)	-0.032***	-0.037***	0.036***	0.024***
	(0.007)	(0.007)	(0.003)	(0.003)
Constant	0.307***	0.343***	-0.055***	-0.022***
	(0.018)	(0.019)	(0.008)	(0.008)
No. of obs.	96,584	96,584	96,584	96,584
Adjusted R^2	0.064	0.073	0.23	0.246
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Notes: All variables are defined in Table 1. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 9: Managerial action channel

Characterisitic	*CScoreHigh*				*GScoreHigh*			
Variable	Large Jumps		Small Jumps		Large Jumps		Small Jumps	
	NLJ	PLJ	NSJ	PSJ	NLJ	PLJ	NSJ	PSJ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PilotFirm	-0.0185***	-0.0192***	0.0075***	0.0066***	-0.0106***	-0.0146***	0.0087***	0.0082***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
SHO	-0.0591***	-0.0469***	0.0412***	0.0385***	-0.0826***	-0.0788***	0.0878***	0.0754***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
SHO × *PilotFirm*	-0.0193***	-0.0104**	0.0159***	0.0231***	-0.0026	0.0051	0.002	0.0054**
	(0.004)	(0.005)	(0.003)	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)
Characteristic	-0.0543***	-0.0573***	0.0354***	0.0325***	0.0432***	0.0434***	-0.0279***	-0.0252***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
PilotFirm × *Characterisitic*	0.0155***	0.0132***	-0.0051***	-0.0044***	-0.0094***	-0.0071**	0.0004	-0.0003
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
SHO × *Characteristic*	-0.0265***	-0.0373***	0.0527***	0.0415***	0.0176***	0.0231***	-0.0359***	-0.0286***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
SHO × *PilotFirm x Characteristic*	0.0138**	0.0148**	-0.0146***	-0.0177***	-0.0190***	-0.0178***	0.0190***	0.0200***
	(0.006)	(0.006)	(0.003)	(0.003)	(0.006)	(0.006)	(0.003)	(0.003)
Constant	0.2471***	0.2835***	0.0229***	0.0242***	0.1964***	0.2313***	0.0558***	0.0541***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No. of obs.	155,459	155,459	155,459	155,459	155,459	155,459	155,459	155,459

Notes:All variables are defined in Table 1. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.